

Aspect-Based Sentiment Analysis on Danantara Policies Using IndoBERT–BiLSTM

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Abstract—This study examines Aspect-Based Sentiment Analysis (ABSA) of public opinion regarding Danantara's policy on platform X, the primary space for public discourse on strategic economic policies in Indonesia. This research matters because conventional sentiment analysis has not revealed the policy dimensions that attract public attention. The research data consists of 14,123 Indonesian-language tweets from February 24–28, 2025. Aspect identification was conducted exploratively using Latent Dirichlet Allocation (LDA) and focused on three main aspects: policy transparency, management effectiveness, and institutional credibility. Sentiment classification at the aspect level was performed using the IndoBERT–BiLSTM model and compared with the fine-tuned IndoBERT model. The test results showed that IndoBERT–BiLSTM achieved an accuracy of 90.83% and an F1-score of 90.86%, higher than the fine-tuned IndoBERT with an accuracy of 89.51% and an F1-score of 89.43%, resulting in a performance increase of 1.32% and 1.43%. Aspect-by-aspect evaluation showed that IndoBERT–BiLSTM achieved 99% accuracy for policy transparency, 95% for management effectiveness, and 94% for institutional credibility, respectively. These findings confirm the effectiveness of the IndoBERT–BiLSTM integration for the Indonesian-language ABSA and are relevant as a baseline for a more targeted understanding of public perception.

Index Terms—ABSA, Deep Learning, LDA, Public Policy, Sentiment Analysis.

I. INTRODUCTION

Social media platform X has become a primary channel for the public to express opinions regarding government policies in Indonesia. One policy initiative that has attracted significant public attention is the Danantara Investment Management Agency (Daya Anagata Nusantara), which was officially launched on February 24, 2025 [1]. Following its launch, social media evolved into an active space for public discourse, revealing diverse public perceptions ranging from support for the policy's national development objectives to concerns related to transparency and institutional governance [2]. This dynamic of public opinion presents substantial potential for computational analysis, particularly to understand societal sentiment toward specific aspects of the Danantara policy. Therefore, an analytical approach is required that not only measures overall sentiment polarity but is also capable of identifying and mapping the specific aspects that constitute the focus of public attention.

Aspect-Based Sentiment Analysis (ABSA) is considered a relevant approach because it enables the analysis of relationships between discussed aspects and their associated sentiment polarity. Through ABSA, public opinions are not merely classified as positive, negative, or

neutral, but are also explicitly linked to particular aspects such as policy transparency, investment efficiency, or institutional credibility. This characteristic makes ABSA superior to conventional sentiment analysis methods, which typically produce global sentiment outcomes without identifying the specific elements that trigger such sentiment [3]. In the context of public policy, an aspect-based approach allows researchers and policymakers to more accurately and deeply understand the sources of public sentiment, thereby supporting evidence-based policymaking [4].

Several recent studies have demonstrated the effectiveness of ABSA across various public opinion analysis domains. An ABSA framework based on Latent Dirichlet Allocation (LDA) and IndoBERT has been applied to identify aspects and sentiment in mental health applications [3]. ABSA has also been employed to assess public satisfaction with electronic-based public services in Central Java [5]. Furthermore, the effectiveness of a lexicon-based ABSA approach has been demonstrated for analyzing sentiment in economic and financial texts by identifying sentiment polarity across relevant topics [6]. An IndoBERT-based ABSA framework has also been utilized to analyze public perceptions of policies implemented by the Indonesian Ministry of Finance, mapping public sentiment across economic, budgetary, staffing, and taxation aspects [7]. These studies indicate that ABSA is an effective method for understanding the structure of public opinion toward complex policy issues.

However, the application of ABSA in the Indonesian language still faces several challenges, particularly due to the limited availability of labeled corpora and the complexity of linguistic expressions commonly found on social media. Informal sentence structures, code-mixing, slang usage, and emojis often cause difficulties for sentiment analysis systems in accurately identifying aspect-sentiment pairs [8]. To address these limitations, models based on Bidirectional Encoder Representations from Transformers (IndoBERT) and Bidirectional Long Short-Term Memory (BiLSTM) can be utilized to strengthen contextual linguistic representations [9]–[10]. IndoBERT is capable of capturing contextual meanings in natural language, while BiLSTM is effective in modeling word sequences and temporal dependencies. The integration of these models offers strong potential to improve the accuracy of aspect identification and sentiment classification, particularly in short social media texts.

Aspect determination in this study is grounded in a review of related research analyzing public perception of investment and economic policies. ABSA has been applied to identify specific aspects of Indian government policies, including economic reform, social welfare, healthcare

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services, and education, to understand their influence on electoral dynamics [4]. In addition, ABSA has been utilized to evaluate smart government services by identifying aspects such as service quality and transparency, thereby supporting improvements in citizen satisfaction [11]. An IndoBERT-based ABSA framework has also been employed to analyze public perceptions of policies implemented by the Indonesian Ministry of Finance, identifying aspects related to economic, budgetary, staffing, and taxation issues through Twitter data [7]. These studies demonstrate that ABSA provides fine-grained insights into public opinion by identifying policy-specific aspects, making it suitable for analyzing complex government policies. Based on the similarity of public policy contexts and discourse characteristics, this study adopts policy transparency, management effectiveness, and institutional credibility as the primary aspects for analyzing public opinion on the Danantara policy. The selection of these aspects is further supported by preliminary observations of the dataset, indicating that these three aspects consistently emerge in public discourse surrounding government investment policies.

Motivated by the limitations identified in previous studies, this research proposes a hybrid framework for ABSA to analyze Indonesian public opinion regarding the Danantara policy. Unlike previous studies that primarily focused on document-level sentiment classification or employed a single deep learning architecture, the proposed framework integrates LDA for exploratory aspect identification with the IndoBERT-BiLSTM architecture for aspect-level sentiment classification [9], [12]–[13]. This integration combines contextual semantic representations with sequential feature learning, enabling the model to better capture aspect-specific sentiment in Indonesian social media texts. Furthermore, the study provides a fine-grained sentiment analysis across three policy-related aspects, namely policy transparency, management effectiveness, and institutional credibility, thereby extending conventional sentiment analysis toward more comprehensive policy-oriented insights.

The main contributions of this study are threefold. First, this study proposes a hybrid LDA-IndoBERT-BiLSTM framework for Indonesian aspect-based sentiment analysis that combines exploratory topic modeling with contextual deep learning to improve aspect-level sentiment classification. Second, the proposed model is comprehensively evaluated against a Fine-Tuned IndoBERT baseline using multiple evaluation metrics and is further validated through McNemar's statistical significance test to confirm the effectiveness of the proposed approach. Third, this study provides fine-grained sentiment insights into public opinion on the Danantara policy, offering empirical evidence that may support evidence-based policymaking and demonstrate the applicability of hybrid transformer-based architectures for Indonesian ABSA tasks.

II. RELATED WORK

Aspect-Based Sentiment Analysis (ABSA) has gained significant attention due to its ability to provide more fine-grained sentiment insights compared to conventional

sentiment analysis. Transformer-based deep learning models have been shown to outperform traditional architectures, such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), in capturing the relationships between aspects and sentiment expressions [14]. Their findings emphasize the importance of contextual representations in improving aspect-level sentiment classification performance.

A systematic literature review has shown that most ABSA studies focus on English-language datasets and product or service review domains [15]. Applications of ABSA in public policy contexts and Indonesian-language texts remain relatively limited. This gap highlights the need for further research in multilingual and domain-specific ABSA, particularly in the context of Indonesian social media texts, which are often informal and linguistically complex.

In the Indonesian context, deep learning approaches have been applied to ABSA across various domains. Deep learning techniques have been implemented for ABSA on hotel reviews [12], while a Bidirectional Long Short-Term Memory (BiLSTM) model has been employed to analyze tourist attraction reviews [16]. These studies demonstrate the potential of deep learning models for capturing contextual information and improving aspect-level sentiment classification in Indonesian-language texts.

Topic modeling approaches have also been utilized to support aspect extraction in ABSA. Latent Dirichlet Allocation (LDA) has been integrated with machine learning algorithms to enhance ABSA performance on hotel review datasets [17]. Furthermore, LDA has been shown to effectively identify dominant discussion patterns in online media and social media datasets [13], [18]. These findings indicate that LDA can serve as an exploratory mechanism for uncovering latent aspects before performing aspect-level sentiment classification.

Recent research has also explored the application of aspect-based sentiment analysis in public policy and governance domains. ABSA enables researchers to identify which policy dimensions receive positive or negative responses from the public, thereby providing more actionable insights for policymakers. Studies conducted between 2022 and 2024 demonstrated that ABSA can effectively reveal multidimensional public perception in areas such as economic policy, digital governance, and public services [19]–[20].

Recent studies have further emphasized the integration of contextual embedding and sequential modeling for ABSA. The combination of global contextual modeling and local sequential modeling has been identified as an important component of modern ABSA systems [21]. Furthermore, the integration of BERT-based contextual embeddings with a BiLSTM layer has been shown to improve classification performance compared with static embeddings [22]. Consequently, hybrid architectures that combine transformer-based embeddings with recurrent neural networks have attracted increasing attention in sentiment analysis research. In addition, recent studies have indicated that BiLSTM layers effectively capture sequential dependencies that may not be explicitly

modeled during transformer fine-tuning, particularly in short-text sentiment classification tasks [3], [23].

Recent studies have also highlighted the challenges of applying aspect-based sentiment analysis to social media data. Compared to structured review datasets, social media texts often contain informal expressions, abbreviations, code-mixing, and inconsistent grammatical structures, which increase the complexity of aspect and sentiment identification. Several studies conducted between 2022 and 2025 reported that contextual language models are particularly effective in handling noisy short texts due to their ability to capture semantic relationships beyond surface-level word patterns [23]–[24]. In addition, combining topic modeling with deep learning approaches has been shown to improve the interpretability of sentiment analysis results by linking latent discussion themes with predefined analytical aspects. These findings support the use of a hybrid framework integrating LDA and contextual deep learning models for analyzing public discourse on social media platforms.

Although an ABSA framework integrating LDA and IndoBERT has been applied in the mental health application domain, its effectiveness for multidimensional public policy discourse remains underexplored [3]. In the specific context of the Danantara policy, previous studies have been limited to conventional sentiment analysis using traditional machine learning algorithms, such as Support

Vector Machine (SVM) and Random Forest [1]–[2]. These approaches classified sentiment polarity at the document level without identifying aspect-specific sentiments, thereby providing limited insights into which policy dimensions received public support or criticism.

Based on the reviewed literature, research integrating LDA for exploratory aspect modeling and IndoBERT–BiLSTM for aspect-level sentiment classification in Indonesian public policy contexts remains limited. Therefore, this study proposes an integrated framework combining topic modeling and contextual deep learning to provide a more comprehensive and multidimensional analysis of public sentiment toward the Danantara policy.

III. METHODS

This study uses an Aspect-Based Sentiment Analysis (ABSA) approach to analyze public sentiment towards Danantara's policies on social media using IndoBERT and BiLSTM. The goal is to extract important aspects from tweets and determine the polarity of sentiment in each aspect. The ABSA approach was chosen because it allows for more in-depth analysis than global sentiment and supports data-driven decision-making. The flowchart from data collection, preprocessing, topic modeling, feature representation, sentiment classification, data sharing, to model evaluation can be seen in Figure 1.

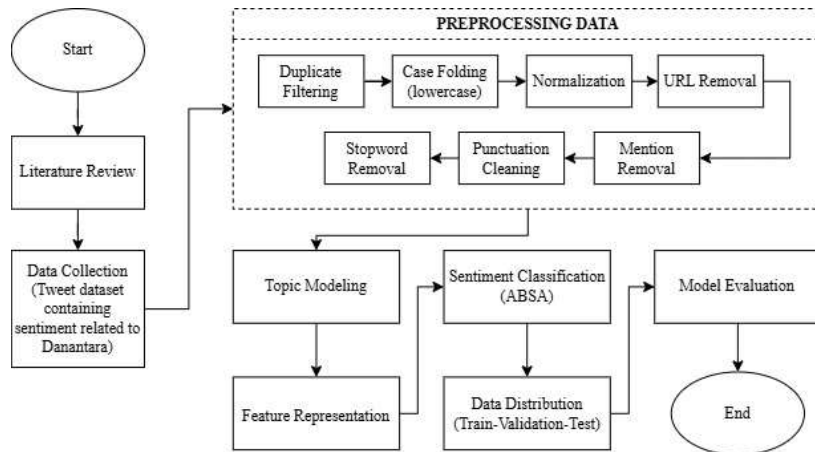


Fig. 1. Research Method Flowchart

A. Data Collection

The data for this research was obtained from a public dataset containing 14,123 tweets about the Danantara policy available on the [Kaggle](#) platform. This dataset was compiled based on keywords related to "Danantara," "BPI," "state investment," and "policy." The data used is in brackets for the period from February 24 to February 28, 2025. Each entry in the dataset consists of full_text, created_at, favorite_count, reply_count, retweet_count, quote_count, location, username, and label. This data is highly variable, both in terms of language, sentence structure, and clarity of context, so a preprocessing stage was performed to ensure the text is ready for use. This stage includes text cleaning, removal of references and links, normalization of informal language, and tokenization for further processing, as shown in Table I.

TABLE I. EXAMPLE TWEETS FROM THE DATASET (TRANSLATED)

username	score	English Translation
budiman.22	2	Danantara has finally been launched! Hopefully, it will become a game-changer for Indonesia's economy ID #BPI #Investment
siti_kritikus	0	Danantara looks promising on paper, but how will it be implemented? Transparency is key! Do not let it become another 1MDB.
ekonom_pro	1	Danantara presents a major opportunity to diversify state investments. However, it requires strict monitoring and oversight from the public.
rakyat_kecil	0	People are struggling, yet state investment funds are being managed by a new institution. Whose money is it, anyway? It is the people's money!
investor_indo	2	Excited about Danantara! This is a positive signal for both local and foreign investors. Economic growth starts here.

B. Data Preprocessing

The collected data is then processed through a data preprocessing stage. This stage aims to clean and improve the data quality, so it is ready for further analysis. The data preprocessing stages are as follows:

1) Duplicate Filtering

This process is carried out to remove duplicate data that can cause bias in model training and evaluation.

2) Case Folding (lowercase)

This process aims to convert all text to lowercase to ensure consistency and prevent the model from treating the same word with different capitalization as a different word.

3) Normalization

This process aims to change words that have different spellings or spelling variations but have the same meaning into a standard form. This stage is very important for Indonesian-language social media data, because users often use non-standard terms, abbreviations, or slang to increase the ABSA accuracy of the model.

4) URL Removal

This process aims to remove all URLs or links in the tweet, as they don't directly contribute to sentiment analysis. Removing URLs cleans up the text and focuses on the main content of the review.

5) Mention Removal

This process aims to remove usernames or user references (*@username*) from tweets to prevent them from influencing sentiment analysis, which focuses on topic content. Removing mentions can improve classification precision.

6) Punctuation Removal

This process aims to remove symbols, excess punctuation, emojis, and non-alphabetic characters that can add noise to the analysis process. This step ensures that the text only contains linguistically meaningful characters to improve model performance.

7) Stopword Removal

This process aims to remove high-frequency but low-information global words (e.g., “dengan”, “ke”, “apa”, “dan” and others) because they do not contribute to sentiment classification. Accordingly, this step employs an Indonesian-specific stopword list rather than English stopwords in order to improve classification accuracy.

C. Topic Modeling

Format After preprocessing, Latent Dirichlet Allocation (LDA) was applied to identify the main aspects discussed in public opinion regarding the Danantara policy. This step aimed to capture dominant policy-related topics and enable sentiment analysis at the aspect level rather than relying solely on global sentiment classification. Previous studies have demonstrated that LDA is effective in uncovering latent discussion patterns from large-scale textual data and can support aspect identification prior to sentiment analysis, particularly in the context of social media and online public discourse [17], [25].

In this study, LDA was employed as an exploratory topic modeling method to extract policy-related aspects and was not intended for sentiment inference, making it suitable for short and unstructured social media texts as an initial analysis stage before deep learning-based sentiment

classification. This approach aligns with prior research that utilized LDA to map dominant themes in public policy discussions and social media content, thereby providing a structured representation of public attention and concerns [13], [25].

The LDA model was trained on the preprocessed corpus, with the number of topics determined experimentally based on coherence score evaluation. Each topic was represented by the ten most probable keywords, which were semantically interpreted to determine the underlying policy aspect. This interpretation process follows a qualitative topic interpretation approach, in which latent topics are analyzed to identify meaningful aspects before performing aspect-based sentiment analysis [13], [17].

Based on the interpreted outputs of the LDA model, three dominant and conceptually validated aspects were defined: policy transparency, reflecting public perceptions of openness and accountability; management effectiveness, representing evaluations of policy performance and implementation outcomes; and institutional credibility, relating to public trust in the integrity and professionalism of the managing institutions. These aspects were established through qualitative interpretation of the topic keywords and subsequently served as the foundation for the aspect-based sentiment classification process.

D. Feature Representation

In this stage, the preprocessed tweet text is transformed into a numerical representation using the IndoBERT base-uncased model (indolem/indobert-base-uncased). IndoBERT is an adaptation of the Bidirectional Encoder Representations from Transformers (BERT) architecture that is specifically trained on large-scale Indonesian corpora, enabling it to capture bidirectional contextual information in Indonesian text [3], [26].

The feature representation process begins with tokenization using the WordPiece tokenizer, which decomposes each word into subword units to handle morphological variations and out-of-vocabulary terms commonly found in Indonesian social media text [19]. For example, compound or informal words can be segmented into meaningful sub-tokens, allowing the model to preserve semantic consistency across diverse linguistic forms.

After tokenization, each token is converted into a numerical embedding through the IndoBERT embedding layer, which consists of token embeddings, segment embeddings, and positional embeddings, similar to the original BERT architecture [19]. The input sequence is processed by 12 stacked transformer encoder layers that employ multi-head self-attention mechanisms to model contextual dependencies among tokens within a sentence [9].

In this study, the maximum sequence length is set to 128 tokens. Tweets shorter than this length are padded, while longer tweets are truncated to ensure uniform input dimensions. Each token is represented as a 768-dimensional vector, corresponding to the hidden size of the IndoBERT base model. The contextual embedding of the special [CLS] token is used as a holistic representation of

the entire tweet, as commonly adopted in text classification tasks [19]. The resulting 768-dimensional feature vector for each tweet serves as the input for the subsequent aspect-based sentiment classification stage. Previous studies have demonstrated that contextual embeddings generated by IndoBERT are highly effective as feature representations for downstream tasks such as sentiment analysis and aspect-based sentiment analysis in Indonesian-language datasets [3], [9].

E. Sentiment Classification (ABSA)

Aspect-Based Sentiment Analysis (ABSA) is an advanced sentiment analysis approach that focuses on identifying sentiment polarity toward specific aspects mentioned in a text, rather than performing global sentiment classification [14]–[15]. In this study, sentiment classification is conducted at the aspect level, where each tweet is analyzed based on the predefined aspects obtained in the previous stage.

The sentiment classification models employed in this research consist of a fine-tuned IndoBERT model and a hybrid IndoBERT–BiLSTM architecture. IndoBERT is a pretrained transformer-based language model specifically designed for the Indonesian language and has demonstrated strong performance in capturing bidirectional contextual information for sentiment analysis tasks [26]. The 768-dimensional embedding vector corresponding to the special [CLS] token is used as a sentence-level representation and is fed into a fully connected layer with ReLU activation, followed by a softmax layer to produce probability distributions over three sentiment classes, namely negative, neutral, and positive.

To enhance the model's capability in capturing sequential dependencies between aspect terms and sentiment expressions, a Bidirectional Long Short-Term Memory (BiLSTM) layer is integrated with IndoBERT. BiLSTM processes textual information in both forward and backward directions, allowing the model to capture contextual relationships that may appear before or after the aspect term within a sentence [16]. In this hybrid architecture, token-level embeddings generated by IndoBERT are passed to the BiLSTM layer, and the resulting hidden representations are aggregated using a pooling mechanism before being forwarded to a dense layer and a softmax classifier. This combination of contextual embeddings and sequential modeling aligns with recent ABSA research trends that leverage transformer-based representations as feature extractors for sentiment classification tasks [22].

F. Data Splitting (Train-Validation-Test)

Data splitting is conducted to ensure that the model can be evaluated objectively and to prevent overfitting. The manually labeled dataset is divided into three subsets with proportions of 70% for training, 15% for validation, and 15% for testing. The loss function used is categorical cross-entropy, with the Adam optimizer employed for parameter updates. The training data are used to train both models (fine-tuned IndoBERT and IndoBERT–BiLSTM)

by adjusting model weights and parameters through the backpropagation process.

The validation data are utilized to monitor model performance during training and to perform hyperparameter tuning, such as adjusting the learning rate and the number of training epochs, without influencing the testing data. The testing data are reserved for the final evaluation of model performance on data that have never been seen during either the training or validation phases. Data splitting is performed while ensuring that the distribution of sentiment classes (positive, negative, and neutral) remains balanced across all subsets. A stratified splitting method is applied to avoid model bias, particularly in datasets with imbalanced class distributions.

G. Model Evaluation

Model evaluation is conducted using the test data to objectively measure the performance of both architectures (fine-tuned IndoBERT and IndoBERT–BiLSTM). The evaluation metrics employed include accuracy, precision, recall, and F1-score for each sentiment class (positive, negative, and neutral), as well as their overall averages.

Accuracy indicates the proportion of correct predictions out of the total number of instances and is defined as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where TP (True Positive) represents the number of correctly predicted positive instances, TN (True Negative) denotes the number of correctly predicted negative instances, FP (False Positive) refers to the number of incorrectly predicted positive instances, and FN (False Negative) indicates the number of incorrectly predicted negative instances [27]. Accuracy is suitable for datasets with relatively balanced class distributions; however, it can be misleading when one class is significantly more dominant than others [12]. Precision measures how accurate the model is when predicting a positive class, for example, positive sentiment, and is defined as follows:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Meanwhile, recall measures the model's ability to correctly identify all actual positive instances and is defined as:

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

These two metrics complement each other. To provide a more balanced evaluation, the F1-score is used, which represents the harmonic mean of precision and recall and is defined as follows:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

The F1-score helps ensure that the model is not only precise (high precision) but also capable of capturing most positive instances (high recall) [16]. A confusion matrix and a classification report are used to visualize and provide a detailed analysis of model performance. The two models are compared based on these evaluation metrics to determine the most effective architecture for aspect-based sentiment classification.

IV. RESULTS

A. Topic Modeling Results using LDA

After the preprocessing stage, topic modeling was conducted using Latent Dirichlet Allocation (LDA) to examine the underlying thematic structure of public discourse related to the Danantara program. In this study, LDA was not employed to generate new analytical aspects, as the research aspects had been conceptually established beforehand. Instead, LDA functioned as a semantic exploration mechanism to identify dominant word groupings within the corpus and to evaluate their alignment with the predefined research aspects: policy transparency, management effectiveness, and institutional credibility.

To determine the optimal number of topics, the Latent Dirichlet Allocation (LDA) model was evaluated using coherence score values across different topic configurations. The coherence score measures the semantic similarity among words within a topic and is commonly used to assess topic quality. Higher coherence scores indicate more interpretable topics. The evaluation was conducted for topic numbers ranging from two to ten. The coherence score results are presented in Table II.

TABLE II. THE COHERENCE SCORE RESULTS

Number of Topics	Coherence Score
2	0.4439
3	0.4485
4	0.4112
5	0.4197
6	0.4086
7	0.4227
8	0.3869
9	0.4056
10	0.3833

The three-topic configuration achieved the highest coherence score of 0.4485 compared to other topic-number configurations. Although the research aspects had been conceptually defined in advance, this evaluation was conducted to ensure that the selected topic structure demonstrated strong semantic quality and internal consistency, as shown in Figure 2.

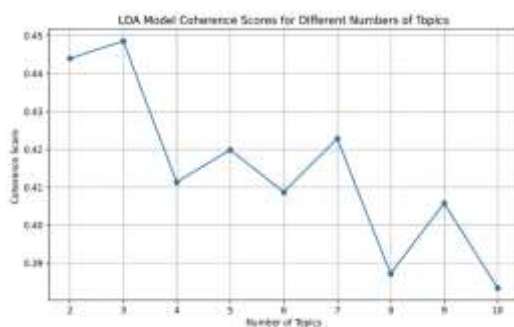


Fig. 2. Coherence Score Evaluation for Different Numbers of Topics

Accordingly, the three-topic model was selected as the optimal configuration, as it empirically exhibited the highest coherence value while also aligning most closely with the predefined research framework. The resulting topic distributions and their dominant keywords are presented in Table III, which subsequently served as the basis for interpretative mapping to the research aspects.

The results of the topic modeling using the LDA approach produced three main topic groups reflecting the

dominant themes in the public discourse regarding the Danantara program. Although LDA is unsupervised and does not explicitly refer to the predefined research aspects, the mapping of topics to these aspects was conducted interpretively based on the distribution of dominant words and the theoretical framework used in this study. WordCloud visualizations of dominant words were employed to strengthen the semantic interpretation of each topic, as shown in Figure 3.

TABLE III. MAIN TOPIC RESULTS WITH WORD DISTRIBUTION

Topic	Dominant Word	Theme Interpretation	Research Aspects
Topic 1	danantara, Indonesia, danantarabangunnegeri, ekonomi, investasi, terpercaya, bpi, nasional, dukung, pembangunan	National development narratives, program support, and the promotion of public trust.	Policy Transparency
Topic 2	danantara, Pertamina, bank, korupsi, bumh, pertamax, biar, banget, orang, uang	Public response to financial and energy management issues.	Management Effectiveness
Topic 3	danantara, Prabowo, presiden, bumh, negara, investasi, aset, badan, dikelola, bpi	Involvement of institutional actors and state asset management	Institutional Credibility



(a)



(b)



(c)

Fig. 3. WordCloud: (a) Policy Transparency aspect, (b) Management Effectiveness aspect, and (c) Institutional credibility aspect

B. IndoBERT Feature Representation Results

After the preprocessing and topic modeling stage, the process continues with feature representation. This stage

involves converting raw text (words or sentences) into numerical forms (vectors) that can be processed by machine learning or deep learning models.

This process begins by transforming text data into numerical representations using the IndoBERT tokenizer. The tokenizer converts each sentence into token IDs, attention masks, and segment IDs that conform to the BERT model input format. Subsequently, these tokens are processed by IndoBERT to generate contextual embeddings with a dimension of 768 for each token. The output from IndoBERT is a tensor with dimensions [batch_size, sequence_length, 768], which is then passed to the BiLSTM layer to capture bidirectional contextual information. The process of transforming text into numerical representations, including tokenization, token ID generation, and attention mask construction, is illustrated in Figure 4.



Fig. 4. Text Transformation Process into Numerical Representation

The architecture used in this study combines IndoBERT as the encoder and BiLSTM as the sequence processing layer. IndoBERT functions to generate vector representations of input text, producing embeddings with a dimension of 768 for each token. These embeddings are then passed to a Bidirectional Long Short-Term Memory (BiLSTM) layer with a hidden size of 128. The bidirectional structure allows the model to capture contextual information from both forward and backward directions of the sentence.

The output of the BiLSTM layer is aggregated using a mean pooling technique to produce a single representative vector for each sentence. This vector is then passed to a dense layer with an output size corresponding to the number of sentiment classes, namely positive, neutral, and negative. The dense layer serves as the final classifier using a softmax activation function to produce probability values for each sentiment class.

This architecture is designed to combine the semantic representation capabilities of IndoBERT with the sequential modeling capabilities of BiLSTM, thus enabling the model to perform more accurate aspect-based sentiment classification, as seen in Figure 5.

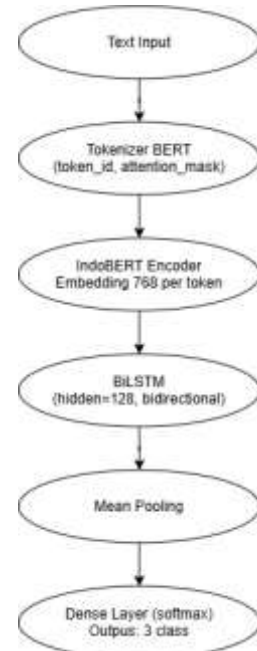


Fig. 5. Text Model Architecture Flow

C. Sentiment Classification Results

This section presents the results of sentiment classification without aspect separation. The purpose of this experiment is to evaluate the ability of deep learning models to classify sentiment polarity in Indonesian tweets related to the Danantara policy. Two classification models were evaluated in this study: Fine-Tuned IndoBERT and IndoBERT-BiLSTM.

Table IV presents the performance comparison between the Fine-Tuned IndoBERT (1) and IndoBERT-BiLSTM (2) models.

TABLE IV. EVALUATION RESULTS OF MODELS

Model	Accuracy	Precision	Recall	F1-score
(1)	0.90	0.89	0.88	0.89
(2)	0.91	0.89	0.89	0.89

The results show that both models achieve good performance in sentiment classification tasks. The Fine-Tuned IndoBERT model achieves an accuracy of 0.90, while the IndoBERT-BiLSTM model achieves an accuracy of 0.91.

The training processes of both models are illustrated in Figure 6. The training and validation accuracy curves show that both models converge steadily during the training process, indicating that the models are able to learn meaningful patterns from the dataset. The IndoBERT-BiLSTM model demonstrates slightly more stable validation accuracy compared to the Fine-Tuned IndoBERT model, suggesting better generalization performance.

To verify whether the performance improvement achieved by the proposed IndoBERT-BiLSTM model is statistically significant rather than resulting from random variation, McNemar's test was performed to compare the prediction errors of the Fine-Tuned IndoBERT and IndoBERT-BiLSTM models on the same testing instances. McNemar's test is a widely used statistical procedure for comparing the predictive performance of two classifiers evaluated on paired observations and has

been recommended for validating differences between classification models [28]–[29]. The contingency table used in this analysis is presented in Table V.

TABLE V. CONTINGENCY MATRIX OF McNEMAR'S TEST BETWEEN INDOBERT AND INDOBERT-BiLSTM

	IndoBERT-BiLSTM True	IndoBERT-BiLSTM False	Total
IndoBERT True	1.520	25	1.545
IndoBERT False	160	106	266
Total	1.680	131	1.811

Based on the contingency table, McNemar's test produced a chi-square value of 97.06 with a p-value < 0.0001. Since the p-value is substantially lower than the significance level of 0.05, the null hypothesis is rejected, indicating that the difference in classification performance between the two models is statistically significant. Therefore, the improvement achieved by the proposed IndoBERT-BiLSTM model is unlikely to have occurred by chance. The results demonstrate that incorporating the

BiLSTM layer significantly reduces classification errors compared with the Fine-Tuned IndoBERT baseline, providing statistical evidence that the observed improvement is meaningful rather than the result of random variation.

While Fine-Tuned IndoBERT is capable of capturing contextual semantics through transformer-based embeddings, it does not explicitly model sequential dependencies between tokens after the embedding stage. In contrast, the BiLSTM layer processes contextual embeddings sequentially in both forward and backward directions, allowing the model to better capture relationships between words within a sentence.

Although the improvement in accuracy appears relatively small, the IndoBERT-BiLSTM model provides more consistent performance across sentiment classes, as indicated by balanced precision and recall values. Based on these results, the IndoBERT-BiLSTM model was selected as the final classification model for aspect-based sentiment analysis.

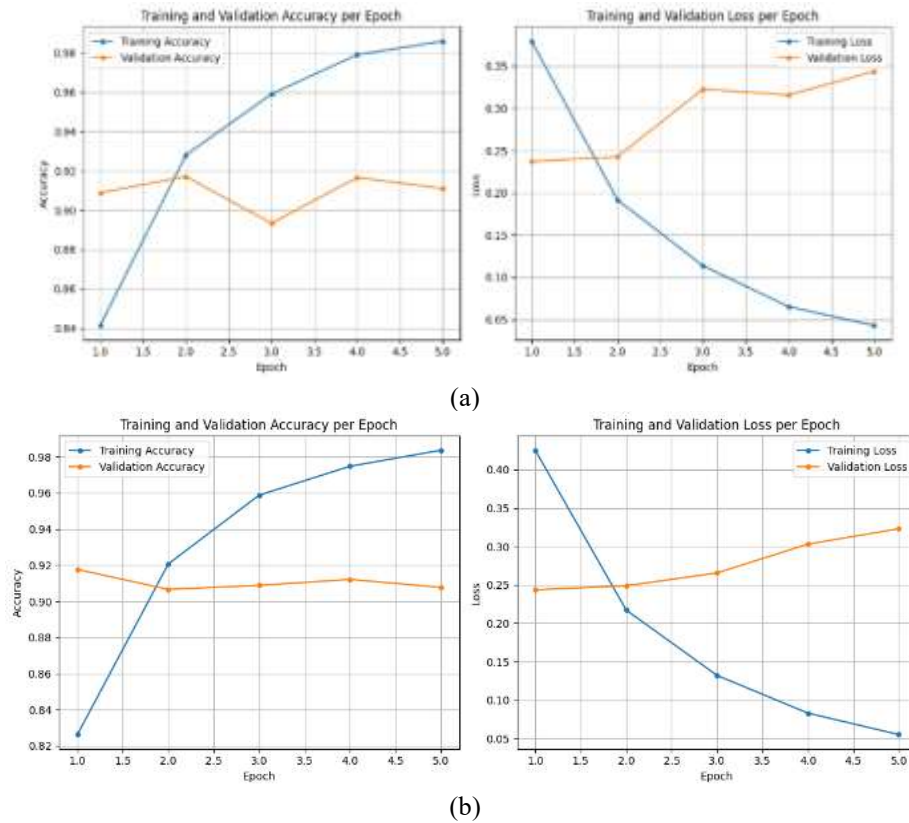


Fig. 6. Training and validation accuracy curves: (a) Fine-tuned IndoBERT and (b) IndoBERT-BiLSTM.

D. ABSA Classification Results

This section presents the results of aspect-based sentiment analysis (ABSA) using the IndoBERT-BiLSTM model. In this task, each tweet is classified based on both aspect category and sentiment polarity. The predefined aspects were determined based on theoretical considerations and supported by topic modeling results.

The performance of the proposed IndoBERT-BiLSTM model was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. These metrics were used to assess the effectiveness of the model in performing aspect-based sentiment classification on

Indonesian-language tweets. Table VI presents the classification results of the proposed model.

To obtain a more detailed evaluation, the classification performance was further analyzed for each aspect category, namely policy transparency, management effectiveness, and institutional credibility. The evaluation results for each aspect are presented in Table VII.

The results show that the IndoBERT-BiLSTM model achieves high classification performance across all aspect categories. The highest accuracy is obtained in the policy transparency aspect with an accuracy of 0.99, indicating that sentiment expressions related to transparency are relatively clear and consistent in the dataset.

TABLE VI. ABSA CLASSIFICATION RESULTS

No.	Original Text	Preprocessing Text	Aspect	Label
1	Geng ibu ² solehah di circle-ku akhirnya mulai goyah u/ pindah dari BSI karena Danantara padahal BSI declare blm ikut programnya. Pada bilang ga redhooo kalau tabungan pendidikan anak & hajinya dipake pemerintah. Sebagai teman yang baik aku hanya bisa menyarankan BCA Syariah	geng solehah circleku goyah u pindah bsi danantara bsi declare blm programnya bilang redhooo tabungan pendidikan anak hajinya dipake pemerintah teman menyarankan bca syariah	Management Effectiveness	0
2	WKWKWK Ternyata kemarin ihsg menguat bukan karena danantara tapi lebih ke kurs kita menguat	kemarin ihsg menguat danantara kurs menguat	Management Effectiveness	1
3	@Riordiscuss @NenkMonica hanya ordal yg skrang bisa langsung duduk kalo cuman danantara aja gmpang level ffffa aja bisa jdi koq	inga inga bayarbayar lupakan nasabah jiwayasa sdh thn polis jatuh tempo danantara bayarbayar jiwasrayagelap ojkabutijinusahajiwayasa	Institutional Credibility	1
4	@machrilmachril1 @prabowo INGA INGA bayar..bayar.. Jangan lupa juga nasabah #Jiwayasa yg sdh 7thn polis jatuh tempo #Danantara @jokowi @smindrawatii @ojkindonesia @Jiwayasa @prabowo @erickthohir @riekediahp @Jiwayasa #Bayarbayar #JiwayasaGelap #OJK_Cabut_Ijin_Usaha_Jiwayasa https://t.co/JfikcP5d0Q,1894175408305606693	dasi nyata hadapi tantangan pembangunan nasional danantarabangunnegeri danantara terpercaya	Policy Transparency	2
...				
12,071	@realfedinuril @CutSarina5 BUMN nya rugi bagaimana Danantara bisa mengambil keuntungan dari BUMN yang merugi setiap tahunnya ? Berita dan data pemerintah kita sepertinya bohong semua? Tidak ada yg bisa dipercaya ? https://t.co/zTvhfz3SJd,1895275662367433063c	bumn rugi danantara mengambil keuntungan bumn merugi tahunnya berita data pemerintah bohong dipercaya	Management Effectiveness	0

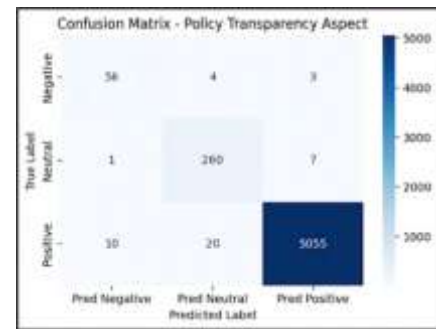
TABLE VII. INDOBERT-BiLSTM MODEL EVALUATION RESULTS PER ASPECT

Aspect	Sentiment Class	Precision	Recall	F1-Score
Policy Transparency	Negative	0.84	0.89	0.86
	Neutral	0.92	0.97	0.94
	Positive	1.00	0.99	1.00
	Accuracy			0.99
Management Effectiveness	Negative	0.96	0.98	0.97
	Neutral	0.95	0.93	0.94
	Positive	0.92	0.87	0.89
	Accuracy			0.95
Institutional Credibility	Negative	0.94	0.97	0.95
	Neutral	0.94	0.95	0.94
	Positive	0.96	0.86	0.91
	Accuracy			0.94

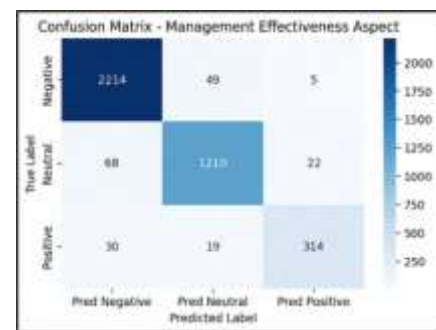
The management effectiveness and institutional credibility aspects also show strong performance with accuracies of 0.95 and 0.94 respectively. Slightly lower recall values in the positive sentiment class indicate that positive opinions are sometimes expressed using more varied linguistic patterns.

Overall, the results indicate that the proposed IndoBERT-BiLSTM model is effective for performing aspect-based sentiment classification on Indonesian social media texts related to public policy discussions. The results indicate that the IndoBERT-BiLSTM model achieves reliable performance in classifying sentiment polarity at the aspect level. The model demonstrates strong performance in identifying positive and negative sentiments, while neutral sentiment classification shows slightly lower performance. This behavior is commonly observed in sentiment analysis tasks involving social media texts, where neutral expressions often contain implicit opinions or ambiguous linguistic patterns.

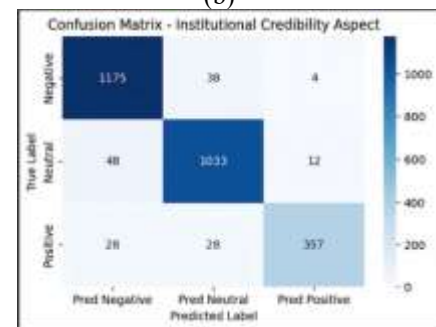
The confusion matrices for aspect-based sentiment classification are presented in Figure 7.



(a)



(b)



(c)

Fig. 7. Confusion matrices of aspect-based sentiment classification: (a) Policy Transparency Aspect, (b) Management Effectiveness Aspect, and (c) Institutional Credibility Aspect

To further investigate the limitations of the proposed IndoBERT–BiLSTM model, representative misclassified tweets are presented in Table VIII. The analysis shows that most prediction errors are associated with complex linguistic characteristics commonly found in Indonesian social media texts. Several tweets contain mixed or implicit opinions, causing the model to emphasize dominant lexical cues while overlooking the overall intended sentiment. In addition, sarcastic or context-

dependent expressions occasionally lead to incorrect polarity prediction. Some factual statements were also misclassified as subjective opinions due to the presence of sentiment-bearing words. These findings indicate that implicit sentiment, contextual ambiguity, and mixed sentiment remain challenging issues for aspect-based sentiment analysis. Future work may address these limitations by incorporating sarcasm detection, richer contextual reasoning, and more balanced training data.

TABLE VIII. REPRESENTATIVE MISCLASSIFIED TWEETS AND POSSIBLE CAUSES

Representative Tweet (Excerpt)	True Label	Predicted Label	Possible Cause of Misclassification
"...Tidak ada ruang bagi penyimpangan karena Danantara memiliki mekanisme kontrol yang ketat."	Positive	Negative	The presence of negative lexical cues such as " <i>penyimpangan</i> " (misconduct) may have dominated the contextual representation, causing the model to overlook the overall positive meaning expressed in the sentence.
"Konsep Danantara itu bagus... masalahnya kita udah kenyang dengan kasus lembaga keuangan dikorupsi massal."	Positive	Negative	The tweet contains mixed sentiment, where an initial positive opinion is followed by criticism. The model likely emphasized the stronger negative context, resulting in a negative prediction.
"Ada Danantara atau ngga gw ga akan mau pake bank BUMN."	Negative	Neutral	The opinion is expressed implicitly without explicit negative sentiment words toward Danantara, making it difficult for the model to distinguish between neutral and negative sentiment.
"Danantara belum keliatan nih, tunggu aja 2-3 tahun lagi langsung ambil alih puncak klasemen."	Negative	Positive	The optimistic lexical expression " <i>ambil alih puncak klasemen</i> " may have been interpreted as positive, while the intended sentiment is sarcastic or ironic.
"Bagaimana iklim investasi di Indonesia akan baik kalau tujuannya hanya untuk dikorupsi... demi suksesnya Danantara kelak."	Positive	Negative	The sentence combines criticism of the investment climate with a supportive expectation for Danantara. The model was influenced by dominant negative terms such as " <i>dikorupsi</i> " and " <i>menabrak hukum</i> ", leading to sentiment leakage.

E. Sentiment Distribution per Aspect

As shown in Figure 8, the policy transparency aspect is dominated by positive sentiment, indicating that public discussions related to transparency tend to contain supportive opinions toward the Danantara policy. The high proportion of positive sentiment suggests that transparency-related information is generally perceived positively by social media users.

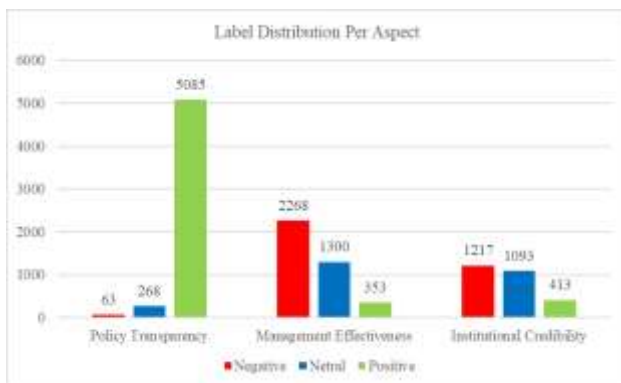


Fig. 8. Label Distribution Per Aspect

In contrast, the management effectiveness aspect shows a higher proportion of negative sentiment compared to other aspects. This indicates that public discussions frequently contain criticism related to policy implementation and management performance. Negative sentiment in this aspect often reflects concerns regarding financial governance and operational effectiveness.

The institutional credibility aspect exhibits a more balanced distribution of sentiment classes, indicating that public perception toward institutional actors is relatively

diverse. Users express both trust and skepticism toward institutions involved in managing the Danantara policy.

V. DISCUSSION

The results of this study demonstrate that the integration of topic modeling and deep learning provides a comprehensive framework for analyzing public opinion toward the Danantara policy. The Latent Dirichlet Allocation (LDA) results reveal that public discussions are primarily concentrated on three dominant themes, namely policy transparency, management effectiveness, and institutional credibility. These findings confirm that the predefined aspects derived from theoretical considerations are relevant for representing public discourse related to government investment policies. The use of LDA as an exploratory method supports the validity of the selected aspects by demonstrating that the dominant topics discovered from the dataset correspond to the theoretical framework adopted in this study.

The sentiment classification results indicate that both Fine-Tuned IndoBERT and IndoBERT–BiLSTM models achieve strong performance in sentiment classification tasks. However, the IndoBERT–BiLSTM model consistently shows slightly better performance than the Fine-Tuned IndoBERT model. This improvement suggests that the BiLSTM layer contributes to capturing sequential dependencies between words that are not fully represented by transformer-based embeddings alone. In aspect-based sentiment analysis tasks, sentiment expressions often appear in different positions within a sentence, and sequential modeling helps the model interpret contextual relationships more effectively. These findings confirm that

combining contextual embeddings and sequential models is an effective approach for aspect-based sentiment classification.

The experimental results also show that the classification performance varies across sentiment classes. Positive and negative sentiments are generally classified with higher accuracy, while neutral sentiment classification shows relatively lower performance. This behavior is commonly observed in sentiment analysis involving social media texts, where neutral expressions often contain implicit opinions or ambiguous linguistic patterns. Informal language usage and short text structures in social media posts further increase the difficulty of distinguishing neutral sentiment from weakly positive or negative expressions.

The aspect-based sentiment classification results provide more detailed insights into public perception of the Danantara policy compared to conventional sentiment analysis. The sentiment distribution analysis indicates that the policy transparency aspect is dominated by positive sentiment, suggesting that discussions related to transparency tend to contain supportive opinions. This result indicates that transparency-related information is generally perceived positively by social media users. In contrast, the management effectiveness aspect shows a higher proportion of negative sentiment, indicating that public discussions frequently include criticism regarding policy implementation and operational performance. Meanwhile, the institutional credibility aspect exhibits a more balanced sentiment distribution, reflecting diverse public perceptions toward the institutions responsible for managing the Danantara program.

These findings are consistent with previous studies demonstrating the effectiveness of Aspect-Based Sentiment Analysis (ABSA) for analyzing public policy perception. The integration of Latent Dirichlet Allocation (LDA) and IndoBERT has been shown to effectively identify aspects and sentiment patterns in Indonesian-language datasets [3]. Furthermore, the integration of BERT-based contextual embeddings with a Bidirectional Long Short-Term Memory (BiLSTM) layer has been demonstrated to improve sentiment classification performance compared with models that do not incorporate sequential layers [22]. In addition, the integration of global contextual representation and sequential modeling has been identified as an essential component of modern ABSA systems [21]. The consistency between the findings of this study and previous research indicates that the proposed IndoBERT-BiLSTM approach is a reliable method for aspect-based sentiment analysis of Indonesian-language social media texts.

Compared to previous studies on the Danantara policy, this study provides a more detailed and multidimensional analysis of public opinion. Previous studies applied conventional sentiment analysis methods that classified sentiment at a global level without identifying aspect-specific opinions. As a result, those studies were not able to explain which policy dimensions received positive or negative responses from the public. In contrast, the aspect-based sentiment analysis approach implemented in this

study enables a more detailed understanding of public opinion by linking sentiment polarity to specific policy aspects [1]–[2].

Overall, the integration of LDA-based topic modeling and IndoBERT-BiLSTM classification provides a comprehensive framework for analyzing public opinion toward government policies. The proposed approach enables both exploratory topic discovery and detailed aspect-level sentiment classification, allowing researchers and policymakers to obtain deeper insights into public discourse. The results demonstrate that aspect-based sentiment analysis offers significant advantages over conventional sentiment analysis in understanding multidimensional public perceptions of complex policy issues.

VI. CONCLUSION

Based on the analysis and experiments conducted, it can be concluded that the proposed Aspect-Based Sentiment Analysis (ABSA) approach using the IndoBERT-BiLSTM model shows promising performance in analyzing public sentiment toward the Danantara policy across multiple aspects. The integration of topic modeling and deep learning classification provides structured insights into public opinion by identifying dominant topics and classifying sentiments at the aspect level. The main conclusions of this study are as follows:

- 1) The Latent Dirichlet Allocation (LDA) method was able to identify dominant discussion topics related to the Danantara policy. The extracted topics reflect commonly discussed issues in the dataset, particularly regarding policy transparency, management effectiveness, and institutional credibility. The WordCloud visualization supports the semantic interpretation of the topics and confirms the relevance of the selected aspects.
- 2) The IndoBERT-BiLSTM model achieved better classification performance compared to the fine-tuned IndoBERT model. The IndoBERT-BiLSTM model obtained an accuracy of 90.83% and an F1-score of 90.86%, while the IndoBERT model achieved an accuracy of 89.51% and an F1-score of 89.43%. This result indicates that the integration of the BiLSTM layer improves the capability of the model in capturing contextual information in sentiment classification tasks.
- 3) The model demonstrated high classification performance across aspects, with accuracy values of 99% for policy transparency, 95% for management effectiveness, and 94% for institutional credibility. However, the dominance of positive sentiment in the dataset caused challenges in classifying neutral sentiment, indicating limitations in data balance and generalization capability.

Regarding applicability, the proposed approach demonstrates the potential for analyzing public opinion on government policies using social media data. However, this study is limited by the dataset size and sentiment distribution imbalance. Future research may consider using larger and more balanced datasets, exploring additional policy aspects, and evaluating the model on

different policy domains to improve generalization capability.

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